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Review

Digital Twin for Human–Robot Collaboration in Manufacturing: Review and Outlook

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Abstract: Industry 4.0, as an enabler of smart factories, focuses on flexible automation and customization of products by utilizing technologies such as the Internet of Things and cyber–physical systems. These technologies can also support the creation of virtual replicas which exhibit real-time characteristics of a physical system. These virtual replicas are commonly referred to as digital twins. With the increased adoption of digitized products, processes and services across manufacturing sectors, digital twins will play an important role throughout the entire product lifecycle. At the same time, collaborative robots have begun to make their way onto the shop floor to aid operators in completing tasks through human–robot collaboration. Therefore, the focus of this paper is to provide insights into approaches used to create digital twins of human–robot collaboration and the challenges in developing these digital twins. A review of different approaches for the creation of digital twins is presented, and the function and importance of digital twins in human–robot collaboration scenarios are described. Finally, the paper discusses the challenges of creating a digital twin, in particular the complexities of modelling the digital twin of human–robot collaboration and the exactness of the digital twin with respect to the physical system.

Keywords: collaborative robot; digital twin; digital manufacturing; human–robot collaboration

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1. Introduction

This new era of industrial digitalization, commonly known as Industry 4.0, focuses on interconnected smart machines [1,2]. Some of the key goals of Industry 4.0 technologies include the development of an open, smart, manufacturing platform, the transformation of machines into a self-aware, self-learning system by allowing each machine to interact with sensors and other machines, and the use of data collected from sensors to aid production and organizational decision making [3]. The application of cyber–physical systems (CPS) along with robotics and digital software technologies, such as computer-aided design (CAD), computer-aided manufacturing (CAM), simulation, system modelling, product lifecycle management (PLM) and enterprise resource planning (ERP) systems are widespread across multiple manufacturing domains. The integration of these technologies forms the foundational architecture of Industry 4.0 [4–6]. Industry 4.0, therefore, enables companies to adapt quicker to the needs of global markets and equips them to face global challenges [7]. The technologies developed as part of Industry 4.0 enable the generation and communication of real-time information about machines, robots and operators. They also enable the development of robots that can work collaboratively with operators.

Robots are used widely in manufacturing to carry out repetitive and strenuous tasks. The size of the global market for industrial robots has been increasing, with almost 2.1 million new robots being installed between 2018 and 2021 [8]. Collaborative robots that can work alongside humans are also used in manufacturing; however, these are designed or programmed to complete a specified task [9]. Collaborative robots use various safety sensors to prevent any hazardous physical interaction with a human. Unlike their industrial counterparts, such robots are much safer and do not require special work cells in which to operate safely. It is expected that in the near future, intelligent collaborative robots and humans will carry out manufacturing tasks by combining their respective skill sets [10].

One of the main concerns with using such intelligent collaborative robots is the safety of the operator while partnering with the robot to carry out the tasks [11]. Safety is an important issue, especially for autonomous robotic tasks in a broad range of applications [12]. One approach to address this problem is to develop a simulation model to replicate and test the actual scenario before it is deployed on the shop floor. This process has been further enabled by the development of IoT and CPS systems that have resulted in high fidelity virtual simulation models capable of acquiring the properties of the physical system. Simulation models that precisely demonstrate a physical system in real-time are known as digital twin (DT) [1,13]. The DT can operate in synchronization with the physical system by utilizing the data acquired and exchanged via the IoT network [14]. DTs, which have evolved using the technological platform of Industry 4.0 [15,16], provide robust models to evaluate, in a virtual manner, the performance of the human and the robot before deploying in the real environment.

In recent years, interest in DT has grown significantly [17]. For instance, the value of the DT market was $2.26 billion in 2017 and is expected to reach $26.07 billion by 2025 [18]. Data gathered from Google trends (Figure 1) illustrates the pattern of individual search terms "DT" and "CPS", with a year-on-year increase evident for DT. It is argued that the concept of DT has gained popularity due to its potential application across a wide range of sectors, including automobile, manufacturing and aerospace [19].

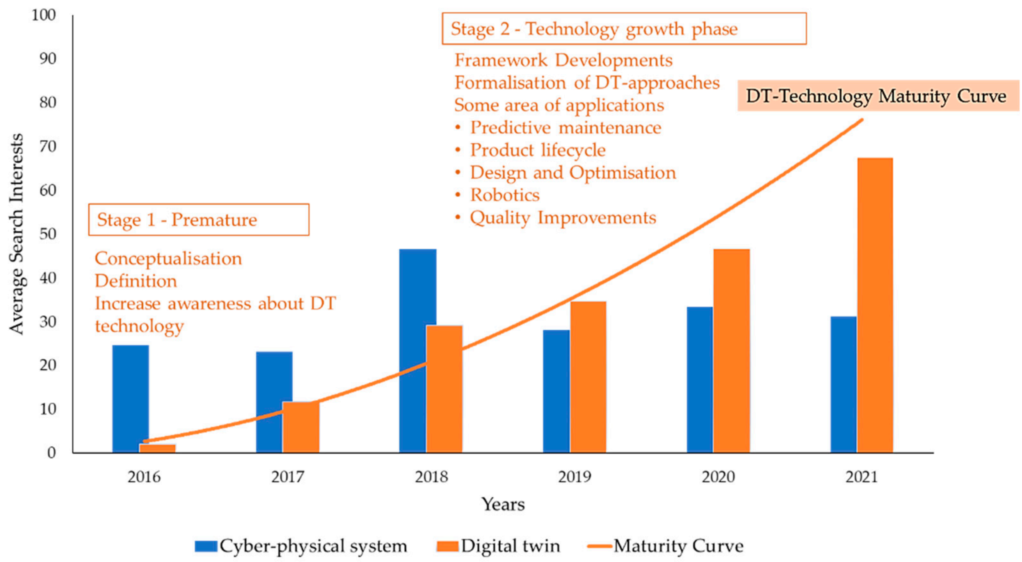

Figure 1. Search interest and technology maturity curve of CPS and DT, since 2016. The graph illustrates the search interest for digital twin (DT) and cyber–physical systems (CPS) in Google search engine from Jane 2016–September 2021. The trend suggests that the focus towards DT is growing. Data source: Google Trends.

Given the range of studies and literature published in the area of DT recently, the focus of this paper is to review the current trends in DT and to discuss the development of DT for human–robot collaboration (DT-HRC) scenarios. Furthermore, this paper provides a review of the various methods that are used in DT-HRC for manufacturing processes. The remainder of this paper is structured as follows: Section 2 provides an overview of DT and HRC, outlining definitions and future potential. In Section 3, the two approaches used to model DT, namely the simulation and layer based approach, are described, with a particular focus on the modelling of human-robot collaboration. Section 4 outlines the challenges facing DT, particularly related to the field of DT-HRC. Finally, the paper concludes with prospects and recommendations for future research.

2. Potential of Digital Twin and Human–Robot Collaboration

Through Industry 4.0 developments, the building of highly accurate virtual replicas of physical entities in manufacturing is now possible, which then enables control and visualization of factory operations [15]. The resulting DTs can be coupled with HRC operation to evaluate and ensure safe cooperation between a human operator and the robot [20]. A DT model consists of a physical environment and a virtual environment. The changes occurring in the physical environment are continuously monitored, tracked and updated in the virtual environment [21,22]. Figure 2 illustrates an abstract representation of a digital twin model of a motor. In the scenario shown, the physical system's (motor) state is captured using sensors and communicated to the virtual model (virtual replica of the motor). The virtual model recreates the exact state and conditions, such as field currents, motor temperature, state-rpm, on/off and computes the motor's efficiency. The value of the process parameters to run the motor more efficiently can also be calculated using this virtual model. Furthermore, the optimal process parameters obtained from the virtual model can be inputted to the physical model to operate the motor more efficiently [23].

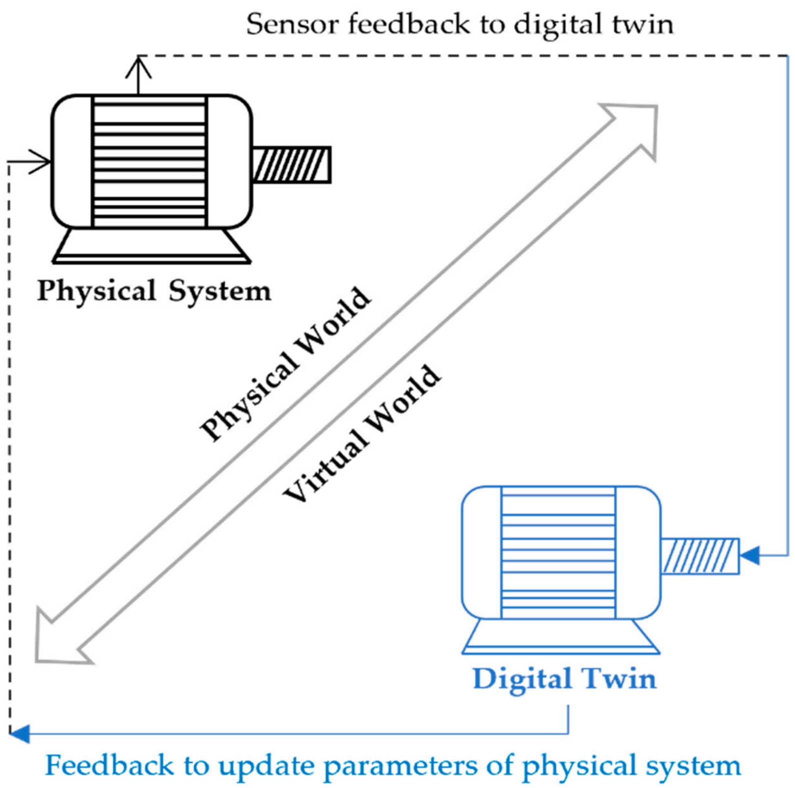

Figure 2. An abstract representation of the digital twin (DT) model of a motor. A DT model recreates real-world entities in a virtual environment with the exact characteristics of the real system. With the information from the sensors, the virtual model will reproduce the exact state and condition of the real-world system.

DT models operate based on multiple underlying components: CAD and CAM data, inventory data, PLM, simulations and real-time sensor information to digitally integrate processes from design to manufacturing, with a seamless transfer of data between systems [24]. DT provides flexibility in simulating and analysing various scenarios without modifying the physical setup or building physical prototypes. It can also support identification of unforeseen issues in the process design. DT can facilitate the early detection of random behaviours and help overcome them at a very early stage [25]. Various companies, such as Dassault, Siemens, ANSYS, Boeing and GE incorporate DT within their business lines [26]. Some of the challenges and requirements of implementing alternative approaches to DT technologies are identified and addressed in [26].

The term DT was presented for the first time at a conference on product lifecycle management (PLM) in 2003 by Michael Grieves. At this stage, DT was relatively immature due to the lack of knowledge in the field [27]. An early DT model was developed by NASA and the United States Air Force for the systems used for aerospace equipment maintenance [13]. The model was subjected to simulated flight conditions and these simulations were carried out using data from an actual space vehicle [28]. In the early stages of its development, the most widely used application of DT was related to identifying faults, performing predictive maintenance, machine health monitoring, performance and quality analysis [29]. Today, as the manufacturing industry is seeking to develop highly automated processes, DT will play an important role, particularly when it comes to collaborative robots. Collaborative robots are robots that are specifically designed to work alongside humans without the need for any safety or protective barriers that are otherwise present in an industrial robotic system/robotic cell [30]. Collaborative robots are also capable of physically interacting with a human in a safe manner. These capabilities are achieved by using sensors and safety features embodied within the robot to sense the environment, especially the presence of humans and other obstructions, and to act accordingly. Using built-in sensors, data related to the state of the robot joints, compliance control, force, and impedance control is readily accessible and can be utilized for developing a DT.

The concept of collaborative robots was introduced in the automotive industry during the late 1990's to increase the safety, quality, and performance and improve the ergonomics of assembly processes [31]. Since then, the capabilities of collaborative robots have increased over the years, initially from using a single-arm collaborative robot to the use now of dual-arm collaborative robots to perform manufacturing tasks [32,33]. The main advantage of using collaborative robots within the manufacturing sector is their ability to work together with the operator without the necessity of being located in a secure enclosure [34,35]. The terms collaboration and cooperation represent two different aspects of HRC. Collaboration means working together to achieve a common goal, whereas cooperation means when the operator and robot work together to achieve a shared goal [36]. Furthermore, depending on the scenario, the relationship between humans and robots can be classified as coexistence, interaction, cooperation and collaboration [37].

Conventional human–robot interaction approaches often lack feedback about the environment around the robot, which can cause stress and fatigue to the operator [38]. On the other hand, the symbiotic HRC approach involves sensors that offer more information about the environment, leading to better planning of tasks, ease of programming the robot, natural form of interaction and decision support [35]. As a result, much of the research related to HRC aims to achieve improved communication and task planning [39], interaction [40–42], trust between the robot and the operator [10,34], and safety [34,41]. Recent developments in the area of industry 4.0 [43], artificial intelligence (AI) [40], DT [22], non-invasive operator tracking utilising sensors such as somatosensory systems [44], wearable devices and vision-based tracking [35,45], and augmented/virtual reality (AR/VR) [42,43] provide additional mechanisms to increase the safety and efficiency of operations and understanding the intentions of the human operator. They also allow more robust methods for humans and robots to work together in a safe, collaborative environment. Operators tend to hone their skills over a period of time, making them more adaptable to various circumstances and enabling them to make decisions in a continuous and dynamic environment. Furthermore, research in the area of bionics and robotic prosthetics can aid humans to effectively participate in HRC in manufacturing environments [46,47]. However, robots require programming or teaching to handle unexpected situations [35]. Hence, the safety of the operator working closely with the collaborative robots should be carefully analyzed [43]. There are various challenges involved in the modelling of HRC to establish safety and trust between the human and the robot. It is necessary to continuously monitor the activities of a HRC system to make the robots adapt to the operator [10,48]. Therefore, DT in HRC could assist in the development of more reliable and trustworthy collaborative scenarios by planning and testing multiple scenarios and configurations of the HRC system in a virtual manner using a DT model.

3. Review of DT in HRC

3.1. Summary of Publications

To evaluate the academic research carried out to date related to DT in robotics, Scopus and Google Scholar databases were used to obtain data on the number of articles published and related research topics since 2016.

Table 1 outlines the number of publications listed in Scopus, using the keywords "Digital Twin" & "Robotics" and "Digital Twin" & "Human-Robot Collaboration". This search was carried out in September 2021. The results focus on the papers that were published in the engineering domain. Table 1 provides an overview of the categories of research articles available. More than 50% of the documents available in Scopus are conference publications compared to journal publications. The keywords were also used to find the number of publications listed in Google Scholar. These results are shown in Figure 3. Based on the results, it is clear that the number of publications in the area of DT and HRC is increasing.

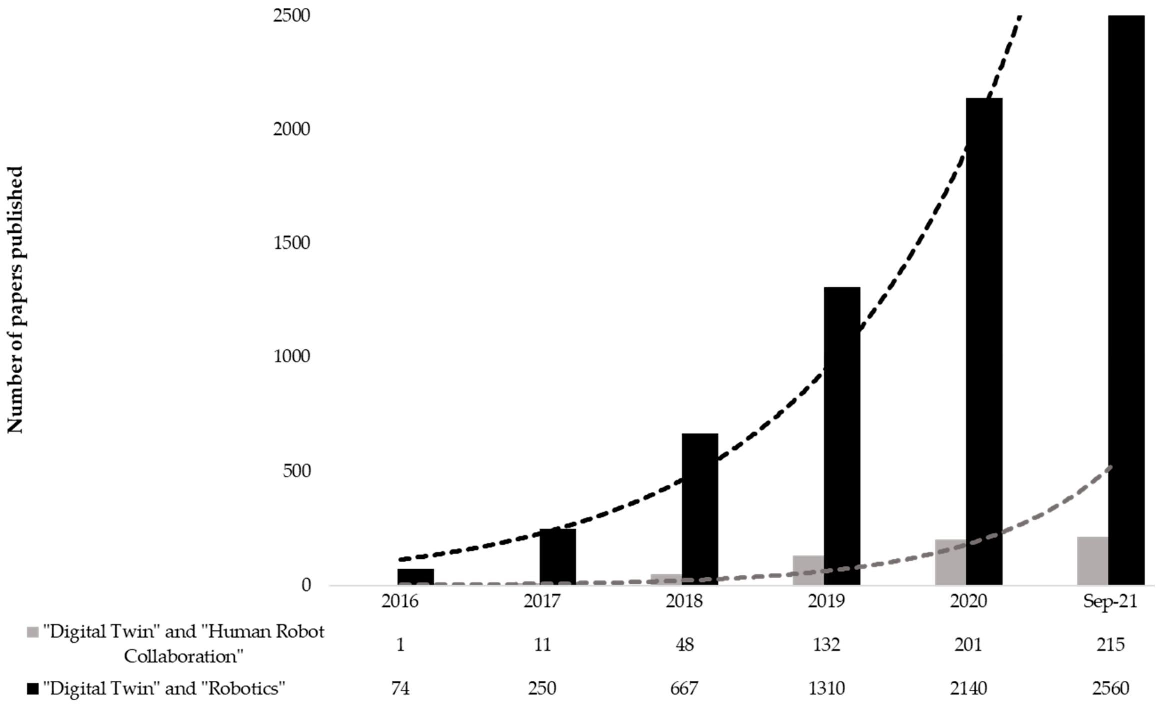

Figure 3. The number of papers found in Google Scholar from the period of 2016—2021. The keyword used for the search is "Digital Twin" and "Robotics" for the data represented in black and the keyword used for the data in grey is "Digital Twin" and "Human Robot Collaboration." The trend line indicates that interest in these areas has increased significantly since 2016.

3.2. Definitions

Though the concept of DT dates back to the early 1990s, the definition of DT was first published in the NASA Modelling, Simulation, Information Technology, and Processing Road Map in 2010 [13,14,49,50]. According to this definition, DT is "An integrated multi-physics, multi-scale, probabilistic simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its flying twin" [51]. The definitions widely used in the literature from 2010 to 2016 are summarized in [13] and from 2014 to 2020 in [52]. There is a wide array of definitions for the term DT in the literature [1,13,17,53,54]. However, the concept of DT lacks clarity in a number of areas, such as the definition, interpretation and implementation. For instance, when DT is compared with system emulation, which is the concept of using an application to imitate a system behaviour, it is defined as "A Digital Twin is the digital representation of a product or system under development representing a functionally correct, predictable and reproducible representation of the product or system at the appropriate level of fidelity to perform verification, performance analysis and system validation tasks" [55]. In summary, a common understanding of the term DT is that it is a high fidelity multi-physics digital model capable of describing the micro and macro features and mirroring the state of and the behaviour of the physical system. DT also has the capability of performing simulation in the virtual model and mirroring the same to the physical model in real-time. Another feature of DT is the two-way real-time communication that exists with the physical system. In general, the definition of a DT tends to be based on an understanding of the concepts, the context and the system for which a particular DT is developed.

Table 1. Scopus indexed publications related to keywords "Digital Twin" & "Robotics", and "Digital Twin", & "Human-Robot Collaboration" in the domain of engineering.

Scopus Keywords	Total Number of Papers	Publication Year and Number of Papers	Source Type
"Digital Twin" and "Robotics"	275	2016—04 2017—07 2018—19 2019—60 2020—95 2021—90	Conference Proceeding—155 Journal—92 Book Series—26 Book—02
"Digital Twin" and "Human-Robot Collaboration"	30	2017—01 2018—04 2019—08 2020—05 2021—12	Conference Proceeding—13 Journal—12 Book Series—04 Book—01

DT can be defined in many ways due to the difference in understanding of DT as a model, simulation technology, or its association with IoT or CPS systems. This difference is based on the level of integration and mode of exchange of data [13,53]. For instance, digital representations such as a digital model, a digital shadow and a digital twin are often confused with one another [1]. Figure 4 illustrates the distinction between these three in the mode of exchange of data between the physical and virtual models. There are two modes of data exchange, namely manual and automated. A change in the physical model that automatically updates the virtual model and vice versa is defined as an automated data exchange, whereas when the physical model does not update changes observed to the virtual model and vice versa, it is described as manual data exchange [1]. Although the underlying functionality of CPS and DT is to integrate the physical and the virtual world, the critical difference between them is the relative focus of each of the technologies. The core of the DT relies on the virtual model and the data to model the characteristic behaviour of the product, whereas the core of CPS involves the integration of the sensors and actuators [27].

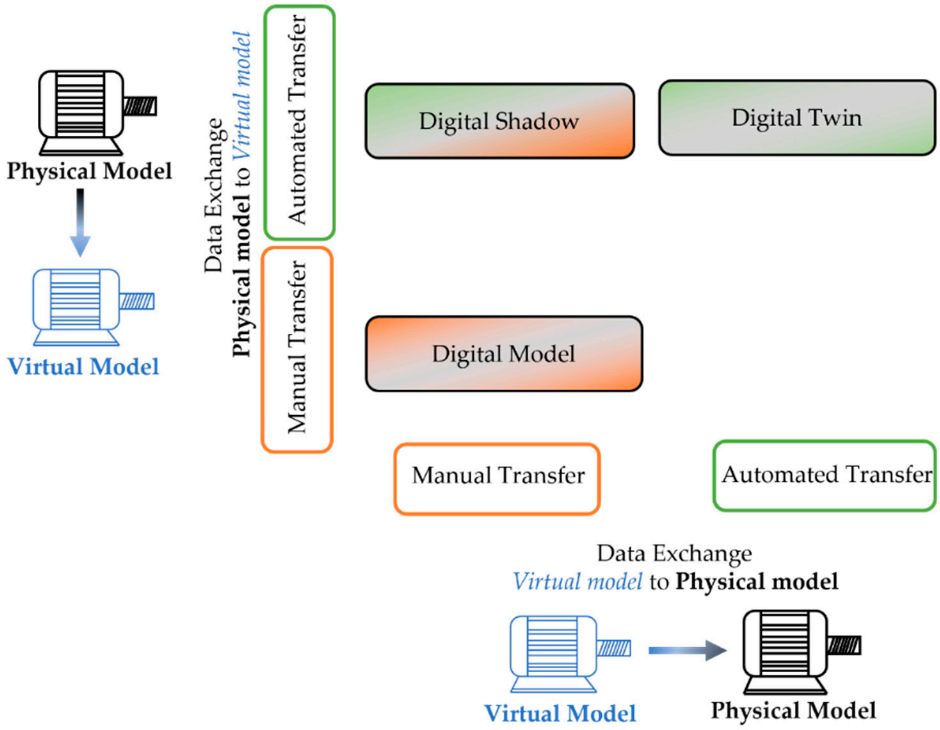

Figure 4. Representation of transfer of data between the physical model and the virtual model.

In a digital system, the type of exchange of data describes the form of the digital system. The mode of interaction and exchange of data between the physical model and the virtual model can be manual or automated. If the transfer of data between both the models is manual, it is known as a digital model. Likewise, if the exchange of data between the models is automated, it is known as a digital twin. Finally, if the data transfer from the physical model to the virtual model is automated and not vice versa, it is called a digital shadow [1].

3.3. Approaches in DT

A DT which focuses on a model-based simulation that integrates the manufacturing processes with the entire product lifecycle is the next wave in modelling, simulation and optimization in the manufacturing domain [28]. However, some researchers conceptualize DT as a system that incorporates the physical characteristics to the digital/virtual counterpart via sensors that capture and exchange data to the virtual world, thereby replicating the characteristics of the physical model in a virtual environment [14,21]. A structured approach to review DT concepts in the manufacturing domain is shown in [17]. This work systematically reviews the current status of DT in the manufacturing domain by providing an overview of the concepts, classification of literature, product lifecycle for applications and direction for further research. The DT of a specific system or an object can be classified into two categories: (i) DT Prototype—consisting of all necessary information to develop a physical model which can be connected to a virtual model such as a CAD model, or (ii) DT Instances—a DT of a model which is connected to the physical product throughout the entire lifecycle of the product, such as geometrical information or operational states from sensors [52,56]. Therefore, the concept of DT can generally be classified into two categories; simulation-based approach (SBA) and layer based approach (LBA). This classification of DT into two approaches is based on understanding from the different streams of literature that address various stages of the product development process involving DT. However, there are different aspects within these two approaches to create a DT. These two approaches, their variants, comparisons and underlying logic are explained in the following sub-sections.

3.3.1. Simulation-Based Approach

The simulation-based approach (SBA) combines the digital models and the data generated at each stage of the product development lifecycle to build the DT [23,28,49,57]. For this, the real-world object's physical, geometrical and behavioural properties are required. Figure 5 gives an overview of the various steps in the development of DT via SBA. The SBA primarily focuses on the collection of data via multiple simulation models at various phases of the product lifecycle, such as the design, engineering, operation and service phases. SBA uses a linear approach where the information gathered at each stage is used to update the digital twin model and maintain a complete record of the product lifecycle as it evolves [58]. In SBA, the DT evolves with the real product by embedding various characteristics and properties of the product [23]. Additionally, the modules used across all four phases of the DT model in SBA need to recognise the data formats used by all other modules. Therefore, the digital thread will play a crucial role in the future of DT under SBA architecture [23,59,60]. Digital thread and data-driven communication architectures can provide seamless integration and transfer of data across the complete product lifecycle. Digital thread supports the process by having a unified data format with all the information required for the exchange of data between the physical and virtual models of the DT [60].

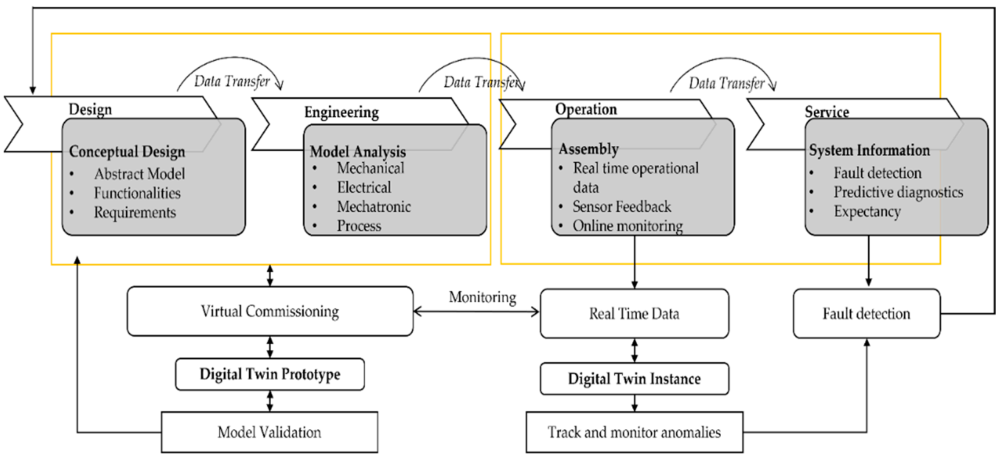

Figure 5. Overview of simulation-based DT. The data collected at each stage of the product development are used to create a digital instance of the physical object. The digital object is developed in parallel with the physical object.

During the development of the DT using SBA, the DT model is commissioned virtually before the operation phase to evaluate the performance and to identify and solve any shortcomings of the model [61–63]. Virtual commissioning can be carried out either by using a hardware-in-the-loop simulation or by using a software-in-the-loop simulation [64]. In a hardware-in-the-loop simulation, the virtual plant is controlled using actual control hardware. In a software-in-the-loop simulation, the virtual plant is controlled by using a virtual controller. A framework that can automate the process of decision making for a simulation-based DT of a CPS is illustrated in [65]. The software-in-the-loop virtual commissioning enables the designer to validate the hardware system before it is manufactured [66]. This is particularly helpful in the case of HRC, as the system can be tested for safety before being physically implemented on the shop floor.

The virtual commissioning of a collaborative robot for a bin-picking application by using software-in-the-loop simulation is explained in [67]. Experimental digital twin, as stated in [68], can be helpful in developing the DT prototype to access and verify safety in HRC scenarios. Furthermore, DT combined with VR can be utilized for safely testing the HRC scenarios [69]. A framework to integrate human–robot simulation with VR is explained in [70]. SBA can initiate multiple DT instances to validate the design, safety and process planning. For example, an event-based simulation model of a DT with a case study of an HRC scenario is discussed in [48]. This study focuses on work-load balances, trajectory optimization and collision avoidance, and shows the capabilities of DT within a HRC scenario. Hence, DT modelling can enable companies to save time and cost in the design of robotic processes [71].

An architecture to implement DT for the controlled flow of information in a smart CPS for planning is discussed in detail in [57]. Here, the foundation level is comprised of the general physical properties of the product, the second level is the interface between the machine and environment, the third level is the reaction or response system, and the final level is the planning. This type of model-based simulation architecture can assist in the preparation of shared tasks between humans and robots in HRC to increase overall performance. The microservice architecture can also be utilized for the modular development of DT-HRC using SBA [72]. A summary of additional articles related to SBA and their application is summarised in Table 2.

Table 2. Summary of strategies and technologies that can potentially be used for building a simulation based DT.

Strategies and Technologies	Conceptual Frame Work	Use Case	Implementation/ Demonstration
Digital thread based approach	[23,59]		[60]
Hardware in the loop simulation	[63]	[68,73]	[61,62]
Software in the loop simulation	[68]	[74]	[66,67,69,75,76]
AR and VR			[69,70]
Data-oriented approach	[65,77]		
DT of manufacturing process		[58,68,73]	[62,69]
Digital factory		[66,73]	[76]
HRC	[63]		[69,70]
Sensor technology	[58]		[69]
Task planning		[73,74]	[70]

3.3.2. Layer Based Approach

The second category, the layer based approach (LBA), describes the design of a DT system generally consisting of three layers [14,21,53,78]. These three general layers are the physical layer, virtual layer and connection layer/information processing layer [79,80]. Figure 6 provides a conceptual overview of modelling the DT-HRC using LBA. The attributes of the physical systems are collected via sensors that are mapped to the virtual system with the help of the connection layer. The connection layer enables the exchange of data between the physical and virtual layers.

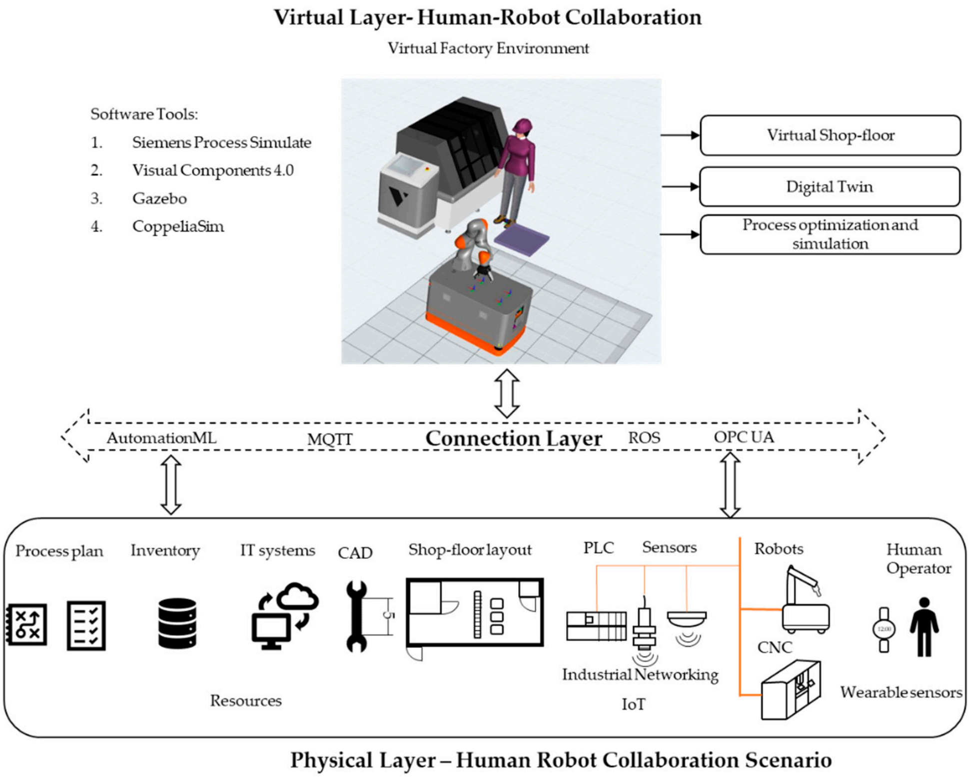

Figure 6. Layer-based approach for modelling of DT in HRC scenario.

The three main layers in LBA are as follows [19,21,29,53,78]:

- Physical Layer
  The physical layer consists of information about the state, the properties of the system and the properties of the environment, collected through various sources such as smart sensors, product development software, resource management and planning tools, networking tools and communication tools. For example, information obtained in the physical layer includes:
  - Design—CAD/CAM, factory layout, drawings of all the physical parts in the production environment;
  - Resources—inventory data, bill of materials, process plan, physical properties of the product, simulation and modelling results;
  - IoT devices—smart sensors, PLC, SCADA, distributed control system (DCS), actuators;
  - Network—communication protocol, machine-machine interface, feedback and control.
- Virtual Layer
  The virtual layer consists of an information model of the physical object and a data processing module [81]. The information model represents the structure of the physical object. The data processing module collects and processes the data about the physical object for real-time reconstruction of the physical object in the virtual world. Hence, the virtual layer represents the digital environment that provides the virtual replica of the object present in the physical layer. The advantage of the virtual layer is that it can create multiple instances of the digital twin model. These multiple models along with the data acquired from the real world can be used to simulate, predict and optimize the process. Additionally, the virtual layer can interact with its physical counterpart to update the system parameters to increase the efficiency of the physical system.
- Connection Layer
  The connection layer acts as a bridge to link the physical and the virtual layer, i.e., it provides an exchange of data between the real-world entities and the digital twin model. This layer handles data storage, processing and communication. The con-

nection layers serve to map the data from the physical layer to the virtual layer and vice versa. The changes can be updated automatically in the physical or in the virtual model. Another purpose of this connection layer is optimization by processing the collected data. The raw data obtained via the sensors are processed to extract relevant information from them. Therefore, various data mining and machine learning techniques are used in the connection layer for process planning, optimization and tracking changes [82].

An improvised model consisting of five layers, i.e., two more layers, namely data and service, on top of the aforementioned layers has been proposed [21]. In this design, the data layer is the core of the system, which interacts via the communication layer to the physical, virtual and service layers in this 5-dimension system. A five-layer approach which is similar to [21] is used in the design of DT for dual manipulator cooperation units [83]. Another five-layer approach is created by dividing the layers into the physical layer, digital layer, data layer, knowledge layer, and social layer [84]. Here, the social layer is similar to the service layer in the 5-dimensional architecture previously mentioned. The service/social layer integrates different services, such as customer relationship management, manufacturing execution system and enterprise resource planning system. The knowledge layer integrated with artificial intelligence capabilities is the brain of the DT. A five-dimensional architecture framework of a reconfigurable DT model using the LBA discussed in [85,86] is similar to that of the SBA. The architecture consists of four layers, namely the physical, model, data and service layer, which are similar to the concept of SBA, namely design, engineering, operations and service. Finally, an 8-dimensional model considering design elements such as hardware, software, IT, computational model, information and intelligence with a focus on intelligence, simulation and model richness is discussed in [87]. This 8-dimensional model is for enabling intelligent DT systems for smart factory applications.

The growth of CPS has contributed significantly towards the realization of building a DT model using an LBA [88]. The data required in the LBA can be grouped into two categories, such as stationery and real-time data. The stationery or non-volatile data are the information that is time-invariant, such as the mechanical design or CAD drawings, and the real-time or time-variant data includes the updates received from sensors on dynamic changes occurring in the shop floor environment [88,89]. An architecture for manufacturing cells in Industry 4.0 that utilizes the IoT gateway, cloud databases and open platform communication (OPC) to collectively combine and transfer data from the physical model to its virtual counterpart is discussed [90]. Table 3 provides a summary of the literature that utilises LBA based approach in various application.

Table 3. Different approaches within LBA using three are more layers.

Layer Based DT	References
Three-Layers	[14,19,29,53,78–82,91]
Five-Layers	[21,83,84,92–94]
Six or more Layers	[87,90]

3.4. SBA vs. LBA Development

The SBA focuses on the integration of various stakeholders in the product lifecycle to share and exchange information at each stage [95]. Therefore, the development of the SBA model is concurrent with each step of the product development from design to engineering to operations and service. The information gathered at each stage of the product development lifecycle can be reused when the product is revised or modified, thereby facilitating modularity [23]. Hence, SBA is more likely to be suitable for new products that are developed from scratch. The data from the initial stages of the design are stored and carried over to create an entire lifecycle of the product with DT [49]. The DT model is tested virtually using VC techniques to analyse the feasibility and cost before the actual start of the physical commissioning of the manufacturing processes [96]. The recent developments in the SBA enable the creation of a DT of existing machines, its reverse engineering for the identification of faults as well as for improving the condition of the machine. Such reverse engineering techniques can be used in the development of DT of older industrial robots to increase efficiency, accuracy and repeatability. The development of such a DT for an existing robotic work cell by utilizing multi-level calibration is discussed in [97].

Although researchers follow both SBA and LBA methods, there is still a lack of clarity on the development of the DT [14]. The development of DT in both SBA and LBA requires information about physical entities, such as material properties, behavioral properties, geometry, sensor attributes, and data management tools. Therefore, an LBA-based approach is more suitable to model the DT of existing manufacturing shop floors. LBA can be used for the development of a digital twin for an existing system which is monitored in real-time and where there is access to the system parameters [98,99]. For example, the LBA of a shop floor can be implemented by utilizing point cloud data from sensors or IoT devices. Such devices can also capture human motion and utilize this data in the DT model [98,100]. The modularity of SBA is favourable for the development of individual products or components, which can be integrated later into a more extensive system such as a digital factory [101,102]. In a digital factory, the lifecycle of the entire system is monitored and tracked to provide additional value to the operation [103]. However, the development process of DT for individual products itself is intense and requires a lot of effort [104]. For instance, the effort to create the DT of a simple casting mould, which has mass and shape properties, shows the difficulty in creating the DT due to non-repeatability inherent with casting [105]. Similar problems may be faced while creating the DT of a manufacturing process. Manufacturing companies often outsource components or sub-assembly manufacturing to third-party suppliers. In such cases, the suppliers should be equipped with the tools necessary to create a DT for the component or sub-assembly being made. The data generated at this stage in the supplier has to be sent back to integrate with the product data. This can be one of the challenges for SBA.

Figure 7 suggests a conceptual framework involving SBA and LBA for developing the DT of a collaborative robot.

- For instance, in the development of a collaborative robotic arm, the information pertaining to each of the joints is gathered, including the motor performance data, efficiency, motor velocities, acceleration, torque, data from force/torque sensors, system information and diagnostic data. As the product is developed, the data at each stage of product development are gathered and stored. These parameters can be updated in a virtual model as its initial parameters. In this situation, the SBA can be used during the development phase of the robot arm.
- Likewise, pre-existing sensors along with additional sensors can be utilized so that the robot may send information about its state to the virtual model. These exchanges of data can be linked together by the data layer, as discussed in the LBA.
- A cloud-based software tool containing the DT model with the actual parameters of the robot can be provided by the OEM such that the end-users can connect the real robot to the virtual model and monitor the DT. This could be useful in a series of tasks including tracking, monitoring and parameterising the robot in order to increase the accuracy, repeatability and life of the real robotic arm.
- Furthermore, an application programming interface (API) can be used to extend the scope of the DT of the collaborative arm across different simulation platforms to create a digital factory environment. Developing the DT concurrently with the development of an actual product can enable faster integration of models to build a digital factory environment.

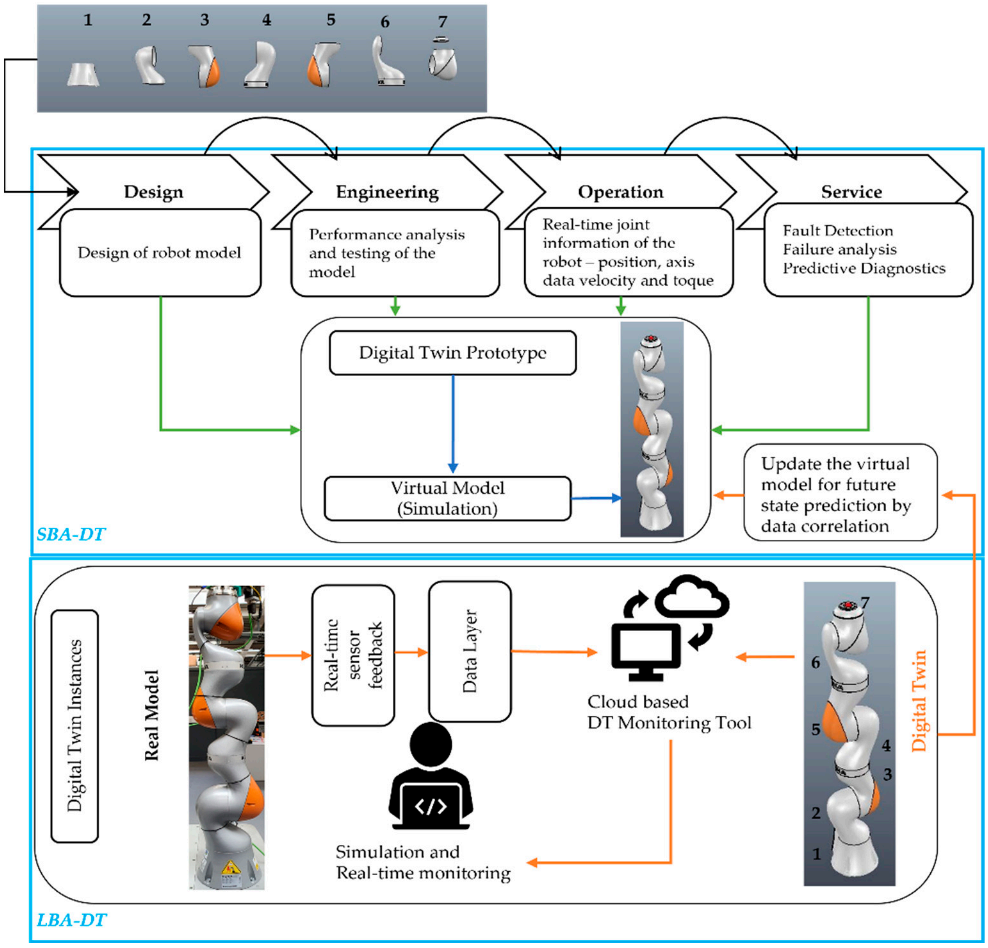

Figure 7. Conceptual SBA and LBA for DT of the collaborative robotic arm. The developed DT can be a part of the digital factory environment.

A conceptual framework highlighted the three main aspects of a HRC, namely awareness, intelligence and compliance [20]. This concept involves the perception of the environment, monitoring, path planning, trajectory optimization, object recognition and gesture/speech-based control to build safety and trust between the human and the robot. This framework, tested using simulation software allowing collaboration between the human and the robot, can be a very useful method to evaluate the performance and trust of HRC-DT during its development phase. Therefore, a SBA based approach can be used for the training, evaluation and optimization of DT-HRC. To model DT-HRC using SBA, a model of the robot, a model of the human, a model of the environment, and a model of the operation/activities performed on the shop floor environment is required. The next step in the development of DT-HRC is to acquire data from sensors to monitor and provide feedback about the operator, environment and process. Therefore, it is essential to develop a system that monitors the real-time attributes of the shop floor and react to the non-deterministic nature of the environment [98]. Visual computing techniques can be used for obtaining partially simulated feedback in real-time about the physical environment by making an operator virtually interact with the collaborative robot [106]. Speed and separation of the operator in an actual scenario can be monitored in real-time and fed back to the virtual environment by using time of flight cameras/sensors attached to the robot [107]. Such time-of-flight sensors can also be used to improve the safety, productivity and performance of the HRC. However, there is no generic architecture in terms of building a DT model [14]. The frameworks used for the development of DT are mainly depended on the requirement and the type of the application.

3.4.1. Software for the Development of Digital Twin for HRC

It is expected that both commercialized software tools and open-source platforms will be used for the development of the DT of a given system. A number of the commercial tools available to create a virtual replica of a robot carrying out the work as well as simulating the same in the virtual environment include Visual Components (VC), Siemens Simatic WinCC and KUKA.Sim Pro [108]. In addition to these tools, game engines, such as Unity3D, have already been used to develop the DT of industrial robots. Here, the motion between the real and the virtual robot has been synchronised and tested [109]. Likewise, tools such as those found in Siemens Tecnomatix are used for simulation of the DT model for optimization, ergonomics, assembly line planning, offline robotic programming and task planning [1,14,22,48,110]. DT using MATLAB is discussed in [111], where the DT of an industrial robot coupled with machine learning algorithms is used to monitor the workspace effectively and avoid collision so that the robotic cell is suitable for HRC applications. Similarly, the DT of an industrial robot using machine vision for autonomous decision making for sorting applications is discussed [112]. This approach uses two packages, Robot Operating System (ROS) and MATLAB, for communication, data handling and motion planning.

Two platforms that are frequently used for experimentation in DT are Gazebo and CoppeliaSim. These two simulation tools can be used with MATLAB and ROS, which provides more flexibility, particularly in modelling humans in the virtual environment [20,98,113,114]. Cloud computing can be used to meet the high computational power required for DT-HRC, as well as to take advantage of readily available cloud-based data processing techniques [115]. Public cloud platforms or open-source cloud platforms, such as OpenWhisk, WSO2, or OpenShift can be used in such instances. However, cloud-based DT can cause communication delays. Hence, these cloud-based solutions can be helpful in processing the non-real-time data and for other non-real-time applications. A framework for integrating DT and web-based technologies is explained in [116].

There are advantages and disadvantages of using open source and commercial software tools for the development of DT-HRC. The cost of the software must be considered when selecting commercial tools. Some commercial software tools offer free licenses valid for a specified trial period for users to carry out initial experiments. Another factor to consider with any software is the learning curve. Commercial tools usually provide standard documentation to get started with the platform. However, to utilize the software to its full potential, the user might have to attend dedicated training delivered by the company, which may incur an additional cost. Another advantage of the commercial platform is the availability of dedicated customer technical support that can assist the user with any technical issues when using the platform. On the other hand, open-source platforms have a very steep learning curve with limited documentation for accessing advanced software capabilities. Some open-source platforms have online communities with supportive users, which can provide quicker resolution to technical problems compared to commercial software tools.

Thirdly, the range of functionality offered by commercial software tends to be better than open-source platforms. Some commercial tools have a library of robot models, grippers and other devices that can be easily imported into the virtual environment. However, tools such as Gazebo require 3D models that are not readily available to be introduced into the simulation environment. In comparison, CoppeliaSim offers some readily available models within the software that can be easily imported into the simulation environment. Commercial platforms also offer various built-in tools for data analytics, such as plotting the joint parameters of the robot [108]. These features can be obtained in open-source platforms but must be programmed to visualise the plot.

The final concern regards the transferability and modularity of the DT model. Use of commercial software tends to restrict the ability to import the data from one platform to another. This can be a potential bottleneck in the development of a complex DT model for the manufacturing process involving several partners. The development of the DT model in an open-source platform can potentially avoid this problem. However, some companies may be reluctant to use non-commercial or open source platforms due to cyber-security and data protection concerns. In addition, there is the issue of computer operating system compatibility, with DT software such as Visual Components, KUKA.Sim, and Siemens Tecnomatix only available on the Microsoft Windows platform.

Example of DT-HRC Simulation vs. Visualisation

For many years, the open-source platform ROS has played an important role in developing various robotic applications and has been widely used in HRC scenarios. For example, a ROS-based architecture of coordinated assembly tasks involving a human and a robot is presented in [117] and a DT involving a dual-arm collaborative mobile robotic platform based on ROS is shown in [118].

There are various open-source or cost-efficient simulation software packages that are compatible with ROS, such as CoppeliaSim, Gazebo, RViz, Unity3D and Blender. Some of these platforms are game engines rather than a simulation environment, but can be used to perform simulation tasks. An example of such an approach has been shown in [109]. A combination of Blender and Unity3D was used to create a DT for a use case to optimize the planning and commissioning process of a production process [119]. While most of these software tools require additional plugins or packages for set-up and visualization, RViz and Gazebo are widely used due to their compatibility with the ROS communication framework. Therefore, for DT-HRC with ROS, simulation and visualization should be considered as two separate tasks.

In order to visualize robotic simulation in RViz or in Gazebo, the model of the robot needs to be imported in Unified Robot Descriptive Format (URDF) or in Xacro (an XML macro language) format. In terms of robotic simulation, each of the joints in the URDF are interconnected as revolute or prismatic joints depending on the type of robot. This facilitates the rotation of each of the individual joints as a single degree of freedom (DoF). However, there are no standard URDF or human mannequins available for RViz or Gazebo. Capturing the motion of operators in real-time using sensors, such as IMU or vision system in Gazebo or RViz is very complex [45]. This is mainly due to the issues related to the creation of floating joints which are typically six DoF joints. The creation of such joints is not supported in Gazebo or RViz. Multi DoF motion cannot be performed without floating joints [120]. Hence, real-time operator tracking in RViz using the multi-DoF URDF model is complex. This is one of the significant drawbacks of real-time monitoring and simulation of human motion in ROS. An approach to overcome this limitation and visualize the operator's real-time motion may be the digital twin of a human avatar created using open-source platforms, such as MakeHuman, Blender and RViz.

An overview of the proposed approach is shown in Figure 8. Here, a human model is created using the open-source platform MakeHuman. This model is then imported into Blender in STL CAD format. The human model is sliced into several parts, as shown in Figure 9, using Blender to create a URDF model. This model is then imported into RViz in the ROS environment for visualization. The proposed approach also involves multiple Azure Kinect sensors, which provide real-time tracking information about the operator. Sensor fusion approaches were used to combine data from these Azure Kinect sensors. The fused data are then used to control the human model in RViz, creating a digital replica of the human that responds to the real time motion of the actual human. ROS provides a package called TF frames, which is used for one-to-one mapping of human joints to the joints of the human model created in RViz. This package facilities the tracking of multiple co-ordinate frames/joints. The body tracking information from the vision system published as MarkerArray (dots shown in Figure 10) is converted and published as TF frames. The number of joints published as TF frames corresponds to the exact number of joints present in the URDF of the human model. Furthermore, the joint name published as TF from the camera should be the same as the human joint's name in the URDF to enable the tracking. So, when the body tracking data and the URDF are launched, these are synchronized and the human motion in real-time can be used to visualize the actions of the operator in RViz, as shown in Figure 10.

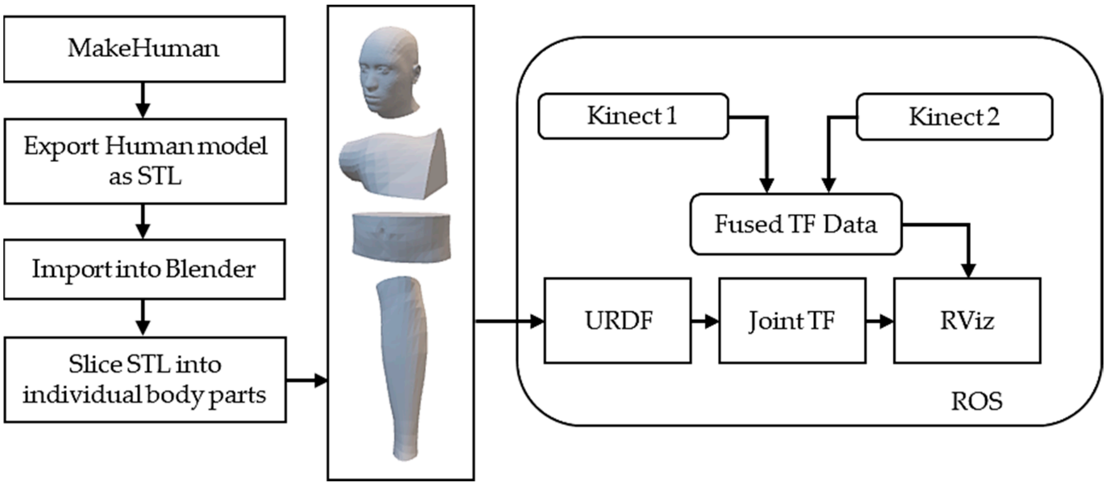

Figure 8. Process of creating a human model for visualisation in RViz.

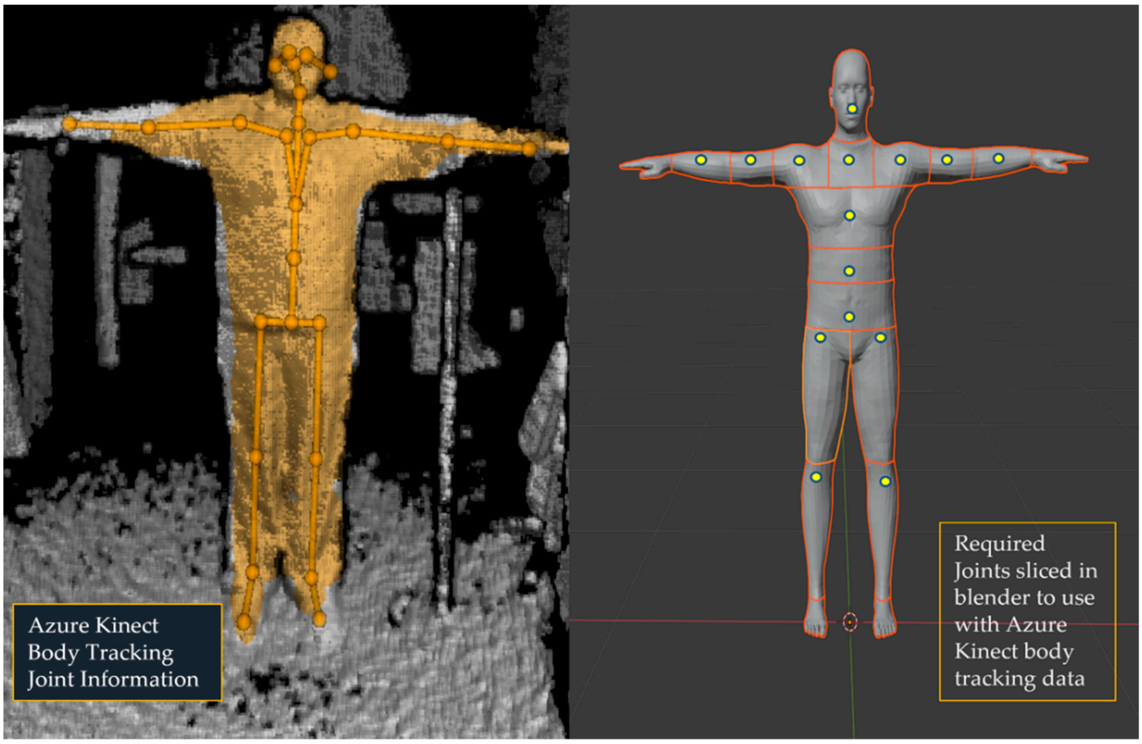

Figure 9. Overview of the model used in RViz for visualisation. (**Left**) shows the skeleton and joint information obtained from the Azure Kinect Camera. (**Right**) A human model developed using MakeHuman and sliced into various parts using Blender. The pictures show the sliced region of the human model used for visualization in RViz.

The section above describes real-time visualization of an operator in RViz. A method involving ROS and Gazebo for human motion simulation for HRC task validation is discussed in [121], where the human motion data are obtained from proprietary software. These motion data are then captured and exported as Biovision Hierarchy (BVH) format, which is used to control the human model in Gazebo. This method facilitates the validation of the HRC process.

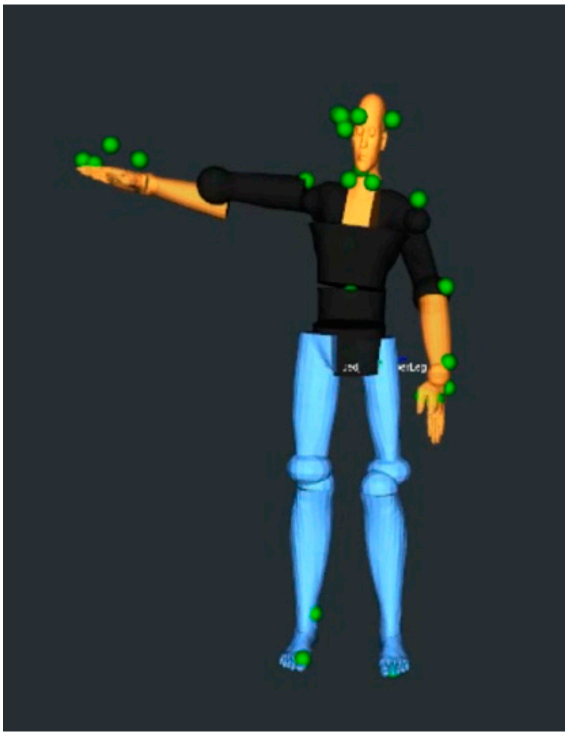

Figure 10. Visualization of the operator (Operator Digital Twin) in RViz. The dots show the MarkerArray published from the vision system.

3.4.2. Deployment and Complexity

In HRC, testing, validation and risk assessment are crucial prior to the deployment of collaborative robots onto the shop-floor alongside operators. The development of VR and AR within the smart manufacturing paradigm enables visualization and interaction with the objects present on the shop floor. The use of the virtual environment, including the uses of AR and VR are explored in [42,122–128] for optimizing the real-world model to support the operator with safety and task flow information. Virtual commissioning in SBA supports the prediction of the operation time and the potential challenges in the real scenario [109]. Therefore, during the VC phase, simulation-based DT coupled with AR/VR technology can assess the safety, impact and risk involved during the actual deployment. This ensures that the system meets the required standards of the factory environment before being deployed [112,122,129]. Several other methods, such as the virtual fence method [123] and remote HRC technique [130] are also being investigated to improve the safety of the operator during the development of DT.

Additional complexity arises with both SBA and LBA related to the flow and integration of data obtained at various stages. The deployment of DT-HRC depends on the acquisition, integration and communication of data from various input modules. Therefore, there are challenges with the integration of various pieces of information across multiple heterogeneous platform models while developing a large-scale DT model such as a digital factory [131]. Data integration techniques developed for CPS have focused on offering a fully interconnected factory environment by connecting all the physical elements and the necessary data. These techniques, such as those used in digital thread, can be useful as a reference in building reliable data integration modules in DT [132,133]. One such example involving the integration of various software tools for a DT of a single robotic cell is shown in [110]. More information on the issues and challenges faced during the development of DT for complex process are discussed in [134]. Here, an architecture framework to build, control and communicate with the DT model is implemented in an industrial environment. Software integration using the standard formats may not be feasible for a DT which is evolving over the product life-cycle [135]. If the development of the DT is based on a standard format, software changes and asset modifications may become cumbersome. Hence, reconfigurable modelling approaches can be used for making the DT adaptable to frequent updates in products, devices, systems and technology [85].

In the future, digital thread can be used to overcome the difficulties with the integration of multiple platforms in the DT-HRC. This can be achieved by a unified data flow that can enable flexible cross-platform communication within the factory shop-floor models. This can also be used as feedback to optimize the performance of the model [60]. Digital Thread, as explained earlier, can provide faster historical and real-time information of the DT model [60].

3.5. Benefits of DT-HRC

3.5.1. Safety

A critical challenge with DT-HRC is to develop a safe environment for the operators to work with the robots as well as to create a sense of trust in order to work together flexibly as a team [22,34,136,137]. The literature which focuses on modelling the human aspect of HRC in DT is comparatively smaller than that which focuses on modelling the DT of the robot [17]. However, in recent years, modelling of the human aspect within the DT has become a more widely researched topic [100,138,139].

In HRC, the interpretation of human motion is challenging. Additionally, the dynamic nature of the shop floor increases the complexity associated with modelling of the collaborative environment [140]. A safe working environment for human operators is essential in HRC. This can be achieved by having feedback that gives an estimate of the approximate positions or the intentions of the operator by using machine learning and AI algorithms combined with non-invasive sensing methods [44,46,47,140–142]. DT-HRC enables machine learning-based approaches to ensure safe HRC via simulation models without altering the physical environment [111]. In this regard, the cognitive symbiotic communication model has recently gained attention. There are a number of other techniques used in HRC for safety purposes. Methods such as voice, gesture, haptic and brainwave perceptions are applied to prevent human–robot collision and to carry out collaborative tasks efficiently [143]. For example, a force-based feedback system is used for the virtual verification of hand guidance control of a collaborative robot in automobile applications [144]. Similarly, vision sensors are widely used with HRC applications to monitor and track the operator and to lower the impact velocity [145]. Additionally, vision-based safety systems can assist in predicting human motion to effectively avoid a collision, optimize the trajectory of the robot, or alert the operator [146,147]. Gesture-based control provides a safe method of interaction between the collaborative robot and the operator [148]. Here, the movement of the operator's arm is tracked to identify the commands from the operator to carry out tasks. Surface-pressure based standing posture recognition system combined with vision-based techniques and deep learning can be utilized to detect the operator's posture and predict the operator's intended action [149].

One advantage of DT-HRC is to effectively validate multiple techniques used in the collaborative scenario and to perform a risk assessment on the model so that the performance of the HRC is optimized before physical implementation on the shop floor. The safety standards formulated for the collaborative scenario determine various factors, such as the minimum safe distance between the human and the robot. The robots are required to take a safe route while working near the operator to ensure the safety of the operator [150]. A kinematic control strategy proposed focuses on the safety of the operator as well as ensuring maximum productivity [151]. Metrics, such as minimum separation distance used can be utilised to compare the results of the DT prototype and DT instances [151]. This strategy can help in optimising the trajectory of the robot so that the robot maintains a safe distance from the operator.

Safety is considered one of the crucial aspects of HRC. As mentioned earlier, it is essential to develop a sense of trust between the human and the robot when tasks are carried out in a shared workspace [136,137,152]. However, the level of safety and trust in a collaborative environment is determined by the programmer who programs the robot. One challenge is the trade-off between robot velocity and safety in the HRC environment. This trade-off is illustrated in Figure 11. The higher the velocity of the robot, the quicker a task can be done, but this leads to lower trust and higher risk for the operator. The DT can be used to find an optimal trade-off between creating a safe environment and minimizing the task cycle time. Reducing the velocity of the robot could potentially stop the robot from being operated at its maximum utility. However, in HRC, the safety of the operator is the prime concern [153]. Hence, for bringing humans and robots together as a team to use their collective intelligence and abilities, both the robot and the human need to be trained together [154]. For this, there is a need to bridge the gap between the way humans and machines are trained. DT-HRC can provide solutions to such problems in a much faster way.

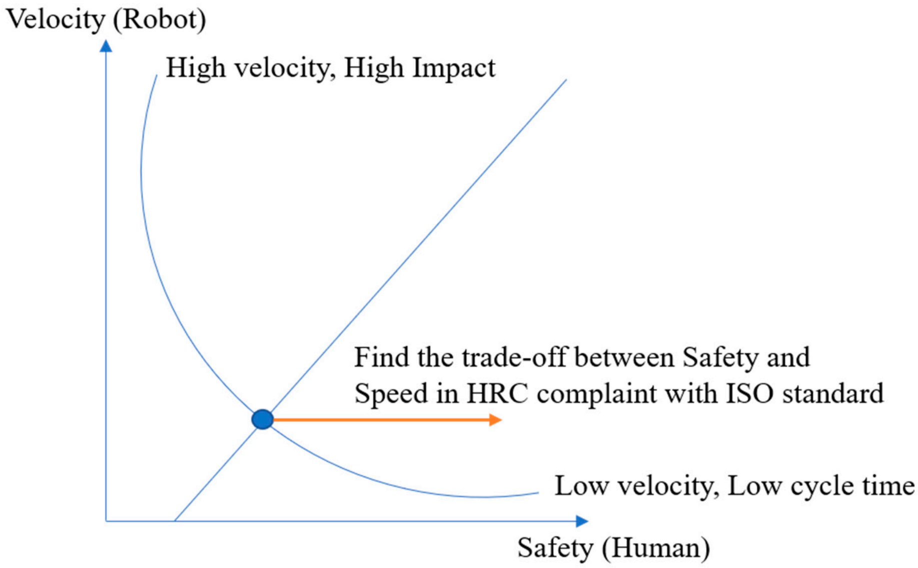

Figure 11. The trade-off between the safety and the velocity of the robot joint in HRC to benefit both the production and safe HRC. DT-HRC can be used to create a model that complies with the ISO guidelines as well as optimize the parameters of the robot in real-time. Various parameters are continuously monitored and measured to meet ISO standards.

In summary, the DT model can be used to evaluate the risk effectively and comply with the safety standards of HRC while optimizing the cycle time. The DT-HRC can evaluate the safety of the system in real-time to monitor the key safety parameters and assist in optimizing speed and configuration of HRC as per safety standards.

3.5.2. Maintenance

DT can support companies in machine health monitoring and maintenance activities. DT models involve vast amounts of data that are collected and processed at various stages to create a high-fidelity simulation model. These data include real-time data, historical data, technical data and service data. The data can be processed to have a layer by layer understanding of the operations, and to study the behaviour of machines in the long run. The focus on the monitoring of machine health and subsequent maintenance planning using data or cloud-based systems has increased due to the development of Industry 4.0 [155]. An approach that combines various predictive maintenance methods, such as statistics-based reliability, physical model-driven and data-driven methods can decrease the error in predictive maintenance [156]. Various sets of experiments can be conducted simultaneously on the DT model to gather information to forecast the failure [157]. Likewise, corrective maintenance using simulation-based DT utilizing the data collected during the engineering phase through production can potentially help minimize the production loss and machine breakdown time.

Moreover, the timing of corrective maintenance can be highly uncertain [158]. Therefore, gathering information across different sensors in the DT model and using data mining algorithms can provide more accurate system failure models and support human decision-making during maintenance tasks. For example, the data acquired from various sensors and the benefits of cloud computing can assist the non-destructive testing and maintenance of machines by providing real-time data for inspection instead of conventional intervention methods. Therefore, data fusion and modelling is a core aspect of DT [159]. DT enables manufacturing companies to focus on product diagnostics and root cause analysis for product quality management [160]. A real-time DT that uses a probabilistic model of the physical system can be utilized to diagnose the physical system [161]. This is achieved by monitoring and comparing the DT and the physical twin in real-time. If the physical twin's behaviour deviates from the predicted behaviours modelled in the DT, then the part in the DT that causes this deviation is further analyzed. Therefore, data from the DT can be utilized to record the physical and digital footprint of the product throughout its product lifecycle [133].

DT involves high fidelity graphical simulation environments that can provide flexibility through the visualization of the assembly of products on the shop floor so that there is a minimum variation between the virtual model and the actual model. This type of DT for geometry assurance has been discussed in the context of smart manufacturing through the process of robotic spot welding [162], which enabled parts to be delivered with higher quality. A framework for using DT for the quality inspection of components in a smart factory scenario to measure the flatness of the component is also possible. The critical technology enabling this is IoT and IoS (Internet of Services) for the creation of DT that acts as a reference model [163]. Emulation software can be used alongside DT to improve the functionality of old machines through reconditioning or retrofitting, a much cheaper process than replacing the old machine [96].

3.5.3. Task Planning and Optimization

The contemporary nature of customer demand requires shop-floor environments to be more flexible and customizable. HRC robots are highly suitable for reconfigurable low-volume production facilities [164]. The rise in the number of HRC tasks within manufacturing facilities where humans and robots share a fenceless environment demands methods to mediate tasks between them. There are various algorithms and decision support systems for task planning and allocation in hybrid and collaborative work cells [114]. The DT of HRC combined with information from the virtual shop floor, virtual world model and the data from the physical world can be utilized to adapt the behaviour of HRC to cope with varying production volumes [98]. The distribution of tasks in HRC will depend on the shop-floor resources. Resource allocation can be formulated as a search problem where an intelligent decision-making system distributes tasks to humans and robots separately [143]. An assembly planning framework that creates a DT of a product from its digital description can perform the virtual assembly of the product and allocate resources accordingly [165]. This approach, coupled with task planning algorithms, can be used to automate the DT-HRC process to efficiently allocate resources and tasks separately to the human and the robot working in a shared space. As the DT-HRC model receives data from various IoT devices, it can continuously update its state and track changes. Furthermore, data can be analyzed efficiently to improve the performance of the physical model [166]. The bottleneck of the process, cycle time and idle time for each task needs to be identified for the adaptation of DT in process planning [167]. A discussion of planning and optimisation of commissioning scenarios where a DT of a process is created is presented in [119].

A DT-HRC testbed implemented to analyze human-robot coordination shows how information gathered across various modules that track human arm trajectory is used with robotic reasoning to identify the tasks that the robot can do without colliding with the operator [168]. Another example of DT-HRC uses an event-based simulation to model workload balancing, task distribution between the robot and the human, and trajectory optimization as per ISO15066 [48]. It also shows the generation of an on-the-fly robotic program to carry out the assigned tasks. Therefore, DT in HRC can be useful for accomplishing complex tasks and building a more robust, safe HRC environment. In addition, DT-HRC enables simulation of the range of states of the robot and the operators as well as the production scenarios that involve various resources to find an optimal solution [22].

3.5.4. Testing and Training

Maintaining a high level of human–robot engagement, enabling a skill-based task distribution between the robot and the human, the adaptation and validation of a workstation layout according to the needs and virtual commissioning requirements of the production system are some of the challenges in designing an HRC system [70]. During the deployment of the HRC system, testing, training and implementation are challenging tasks [122]. This problem is particularly acute when an industrial robot is being modified for collaborative tasks. DT combined with virtual reality (VR) could be a possible solution to this problem [169]. Similarly, AR-based systems can be integrated for DT-HRC tasks [170].

VR is used today to test many CPS and to train operators [171]. In relation to combining VR with DT, it should be noted that a combination of VR with discrete event simulation has already been adopted in many industries [172]. Combining VR with DT will result in a realistic system for operator training [169]. This combination has a series of advantages when it comes to DT-HRC. A major challenge in DT-HRC is the difficulty in developing the DT of the human operator. Combining DT with VR could partially solve this problem. The technologies, software and protocols which are developed for VR could be used in DT and vice versa. This could reduce the cost of developing the DT as the same technology could potentially be used to provide VR solutions.

4. Challenges

Section 3 describes the types of approaches used in the modelling of DT, and compares the benefits of the different methods of DT in relation to HRC. Despite the significant potential for adopting DT-HRC in manufacturing processes, there are challenges to improve the performance of DT. In many cases, DT can become a core component of manufacturing technology, as it can potentially solve a range of problems and lead to the adoption of smart manufacturing [21]. However, the question arises as to whether DT is a panacea for all problems and how widespread the adoption of DT is. Much of the work to date on DT focuses on its use as a model to predict the process and its outcome in the real world, i.e., as a simulation model [173].

The lack of a generic framework model or architecture for the development and implementation of DT is a potential gap that hinders the growth of DT across various applications [14,157]. There are currently no plug and play type modules available to create a DT of any given system. An AutomationML-based concept for plug and simulate provides a proof-of-concept for the automatic setup of the virtual environment by the exchange of XML data from the plant simulation environment [174]. Here, the modular DT interacts with the real-world setup to connect and transfer data, thereby supporting the decision-making process.

Secondly, the lack of structured training programs on DT leads to a shortfall in the skills and knowledge of engineers and developers. Therefore, the lack of adequate knowledge can lead to losses in time, energy and resources in developing a DT model. Hence, there needs to be suitable training and numerous application models to prepare designers and engineers to build the DT model. To achieve this, engineers need to be educated and provided with hands-on experience on DT during their university education. University programmes should promote the use of digital tools wherever possible and improve computer science education in engineering courses, provided that it does not come at the cost of reduced focus on the traditional, core coursework [175]. The challenge here is balancing the fundamental courses in the respective engineering disciplines and the addition of DT computer science-related courses to the curriculum. Strategies for restructuring the courses in engineering programmes should be carried out in view of this potential problem. One way to do this would be to add elective courses related to robotics and DT technologies.

A third challenge relates to the cost of development. The design and simulation of the DT model requires investment in terms of cost, plant downtime and person-hours to implement and deploy DT at various system levels [176]. Furthermore, there are multiple uncertainties involved in creating the model of the system, real-time feedback and interaction between the physical and virtual models.

The success of a DT-HRC relies heavily on how well the HRC system is digitally modelled. One key challenge related to creating the virtual model is that many physical phenomena did not have a good digital model until relatively recently. For example, studies related to the effect of force on materials (fracture, deterioration, etc.) and structures are still in the research phase [56]. Without progress in such fundamental fields, it will be an extremely difficult task for engineers to model the whole system and collect and interpret the data from different sensors. It is expected that Artificial Intelligence (AI) can be utilized to create virtual replicas or virtual models using the data collected from exteroceptive and interoceptive sensors in the HRC system. In such cases, standardization of the data format needs to be carried out in view of DT technology [88]. However, AI is also at the development stage. It is predicted that high-level machine intelligence could be achieved as early as 2040 [177]. For a complex HRC system, creating a DT that satisfies the standard definitions will be difficult. Another issue to consider in the modelling process is the challenges associated with the validation of the models.

The number of possible states the DT-HRC can take at a given time, considering the dynamic nature of the human who is collaborating with the robot is also an obstacle in using the DT-HRC for process optimization. The large number of parameters that affect these types of interactions will increase the number of possible states of the system [56]. There can be thousands of extrinsic and intrinsic parameters that can affect the HRC scenario. Finding all these parameters and simulating the same conditions in the virtual world will be tedious and computationally expensive. The modelling of a human on the shop floor to accurately replicate an exact digital version of an operator in the virtual world is extremely difficult to create. Modelling the digital twin of an operator, incorporating factors related to physical health conditions and emotional aspects, such as trembling, fatigue and emotional distress, to predict the outcome of the activities of the operator is very complex and almost unfeasible, at least, with currently available technologies. Therefore, it is highly unlikely to model the process in DT-HRC utilizing the complete model of operators in a virtual environment.

The number of productive person-hours required to create a DT for simple robot applications, such as a pick and place task, is still unclear. One example is the development of DT that can mirror the exact robot in the virtual world, using a standard robot [83]. This DT provides a set of functionalities, such as plotting the robot data (current, velocity, torque, and motor temperature). However, there are no studies on how this information can be transferred to develop a DT of another robot or on how to model a more complicated process. Moreover, most articles discuss creating a high-fidelity model using DT, but are not clear on how the model should be developed. Likewise, the cost of purchasing and using commercial process simulation software with the required toolbox or plugins to create a DT is expensive. There is still a lack of knowledge and understanding about the concepts of DT, which makes it more challenging for manufacturing industry to implement DT concepts [26].

Fourthly, the integration of DT involves communication and interactions with various CPS and IoT sensors, and therefore requires reliable sensor information and faster updates of real-time data [178]. A potential challenge for implementing the DT-HRC is the problem related to real-time connectivity and synchronization. The lack of high-fidelity models in the virtual environment, along with the other challenges described previously, does not favour the possibility of establishing a closed-loop synchronization of the real and the virtual model. This increases the difficulties of capturing and processing large amounts of data. A reference model or a standard benchmark model is required to overcome these challenges [49]. An attempt to create a DT of a 3D printer showed a delay of 2–3 s to process the data and a 2-s delay in updating the digital and physical model [179]. These authors have also mentioned that their system is much simpler with limited data, and it will be much more difficult to synchronize a complex system. Another important issue to be noted from this research is the 2–3 s computational time required to process the data collected for a system with limited data [159]. This delay is not suitable for real-time control. In another example, the use of a DT to model crack propagation in a single mechanical component having machined features underlines the requirement of high computational power for DT [180]. It took four days to simulate the model when the simulation was running on a high specification personal computer. HRC systems are much more complex than the above-mentioned examples, with many assembled parts, sensors, actuators and other components in a dynamic environment. It is expected that the communication between the physical and virtual world will be much slower and the computational requirements will be multiples of those mentioned in the above literature.

It has been reported that the synchronization and the convergence of the physical and the virtual layer fail to create a detailed simulation model for ultra-high visual analytics of the DT model [48,181]. There are various challenges regarding the use of data analytics and IoT in the context of Industry 4.0 that need to be addressed first before moving on to a photorealistic, fully functional DT of real-time entities and processes [182]. One issue with the IoT and CPS is the compatibility of sensors to integrate old robots or machines. This may lead to the need for new equipment to realize the objective of DT, thereby increasing the cost of the process. As various sensors and modules interact, there is also a concern within the industry regarding the security of networks to prevent cyber-attacks [183,184], leading to another challenge with DT, which is about ensuring the secure real-time interaction between various modules during the exchange of data [173].

Fifth is the accuracy and the precision of the DT simulation model. Currently, most of the DT models create a virtual copy of robots by capturing their motion in the real world and replicating the same action in the virtual world. DT offers the ability to implement various algorithms that can run in parallel without affecting the real-world setup to find the best parameters for optimal results. However, most of these fail to consider the modelling of various complex processes within a DT model, such as wear and tear of the gripper fingers, servo gears, effect of latency between the gripper and the controller and repeatability of the robot over time. An example illustrated in Figure 12 shows a robot involved in gripping an unevenly shaped object. An actual DT of this process must show the actuation of the gripper, wear and tear of the gripper fingers over time, how the object is gripped, the effect of deformities on the object due to gripping force and if the object falls while the robot is motion due to less force. An accurate representation of the process, factoring in many unknown variables, is required to create a highly accurate model of the virtual factory environment [173]. Some of these details are less important than others and can be avoided in a DT. However, the level of precision required of the DT compared to the real world is still unclear. For instance, the DT for geometric assurance in welding focuses on a conceptual framework model and the use of DT to minimize the geometric deviation between the virtual and the real component by using real-time data for optimization [162,185]. However, the optimization of a welding process in real-time is very complicated. It requires high-speed communication and data transfer between the real system and the virtual system. The optimization algorithms should be coupled with Finite Element Method (FEM) software to precisely analyse various parameters, such as ideal temperature, welding sequence and welding positions. In addition, visually representing the outcome of the process as accurately as seen in the real world will be impossible to achieve in the short-term. Moreover, from an industry practitioner perspective, DT is still just used as a simulation model, unlike the full functionality that the DT proposes to offer, with the main objective currently being just to gather data from the physical platforms to control the manufacturing lines, rather than running a virtual simulation in parallel [173].

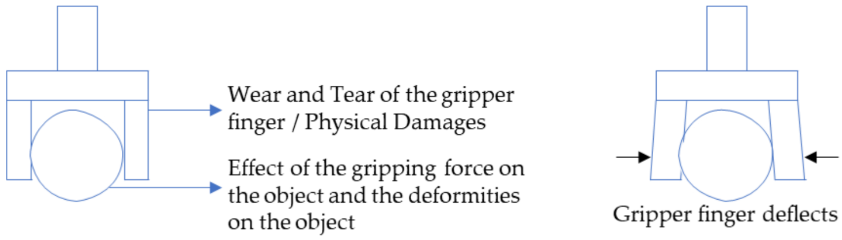

Figure 12. The complexity of modelling DT in robotics. It is still uncertain how DT can exactly represent a real-world process such as wear and tear, physical damages, object deformities, object slip and deflection of gripper finger.

Similarly, the fidelity of the physics engine used for simulation in the virtual environment is an issue, often termed as "the reality gap". While there are many alternative physics engines, all of which are constantly improving, realistic simulation is still a significant challenge. There are ways of offsetting this problem by using more than one physics engine in tandem with one another [186], or the use of algorithms such as grounded action transformation [187] and its variants [188,189]. The stochastic nature of the real world is a particularly prominent issue here [188]. Simulating frictional contact between objects is also a notable issue and this is relevant for robot grasping tasks [190]. For instance, it was found that even small changes in initial conditions could significantly change end results when simulating frictional tasks using common physics engines. These results suggest that a trade-off exists between a simulation's accuracy and its predictability [191]. The performance of different models by simulating several different tasks involving friction (grasping, sliding, wedging and stacking) was examined [192]. Simulating soft robotics is also generally more challenging, particularly when combined with frictional contacts [193]. To deal with these challenges, displaying a confidence value alongside the simulation and letting the user know when a simulation displays accurate results could be a prudent approach [194]. Finally, the challenges around CPS and IoT, such as connectivity, computational power, interaction with various heterogeneous modules involving non-standard communication protocol, may also prevent the creation of a high fidelity virtual model [195].

The adoption of DT across industries also will face challenges because of the design of organizational structures [196]. The typical structure of any organization, including manufacturers of HRC systems, is to have separate sections for research and development, production, finance, marketing and human resources. Research and development could be divided further into different sub-functions, such as design, engineering, etc. Each of these units acts as a silo of information with very little crossflow of information. One department might not use the virtual models and simulations used by another department in the same organization because of the difference in their requirements. To realize the benefits of DT, a unified view of the available information is needed, but internal organizational barriers may hinder this and delay the adoption of DT technology.

The aforementioned challenges can result in a very high cost for implementing DT outside the research laboratory [175]. While research on DT-HRC systems is at a very early stage, it is suggested that the resources and expertise needed for DT will be accessible only by large companies [197].

Though there is growth in the field of computing and other technologies contributing to the development of DT, there is still a lack of clear understanding about what needs to be represented in the virtual world. Furthermore, the lack of training modules and materials on the development of DT adds more complexity and delays in building an exact model. Common approaches and standards among researchers and practitioners need to be developed regarding the expectation and purpose of creating the DT of a particular process.

While digitalization is regarded as the key to the future of the manufacturing industry, and is an area of strategic focus for many [108], most of the DT systems are built on the technological growth and advancement of the Industry 4.0 paradigm [173]. Since it was first introduced in 2011, the concept of Industry 4.0 has evolved and has played a crucial role in the development of manufacturing technologies. Nevertheless, there are still many challenges facing Industry 4.0 that remain unsolved [184,198]. Overcoming these challenges will also benefit DT development.

Human–robot collaboration will play a vital role in manufacturing and assembly processes. Various safety challenges need to be considered to enable a safe human–robot interaction environment [153,199]. DT prototypes can assist with the safe planning of HRC scenarios, while the DT instance can monitor and plan the movement of the robots to ensure real-time safety feedback. However, the degree of fidelity of these simulation models in HRC still lacks clear definition and clarity.

A number of reports suggest how DT can add value to a manufacturing operation and how DT can help solve the problems faced in the manufacturing environment [200–202]. However, DT is a very long way from achieving what it is fully capable of doing. The research reported in the literature either describes examples of different architectures that can be used to build the DT, or demonstrates a DT which captures only a small part of the physical process. Full-scale DTs, incorporating all the essential aspects of a system from control to production management to the collaboration of an HRC employed in a shopfloor, are yet to be developed.

The dynamic updating of the DT model relies on information from various points, such as sensor data, controller data and management tools. 5G wireless network systems that provide low latency and higher bandwidth for faster communication can potentially overcome the challenges faced within CPS and IoT [203]. Therefore, it can contribute to the advancement in DT-HRC technology for manufacturing processes [204,205]. Furthermore, a 5G network coupled with high-performance computing (HPC) and simulation software can potentially improve the fidelity of the DT model, thereby providing a more realistic representation of the real-world model [206]. Additionally, this can enable access to the smart factory paradigm to remotely monitor and control aspects of the real-world model.

5. Outlook and Conclusions

The growth of DT indicates its potential to be an integral part of HRC to support safety, maintenance and task planning. In this paper, we have focused on the impact of DT technologies in the manufacturing domain and various approaches used for creating DT. The research trend shows that the DT is in the technology growth phase and will take many more years to reach maturity. Research on the creation of DT of the industrial robotic process is increasing exponentially, while that of DT HRC is lagging behind. This is mainly due to the fact that it is much easier to create a digital model of an industrial robot than a collaborative robot, due to the uncertainty pertaining to modelling the environment involving the human operator. There are research efforts ongoing to demonstrate the DT of simple robotic tasks with limited sensing capability without considering factors such as ageing and the wear and tear of components. Running a real-time simulation and DT is still a challenge.

Different modelling methods are available for creating a digital model of a task or a process. The integration of models of such processes under one umbrella is essential to create a realistic model of the physical system. Photo-realistic simulation in conjunction with physics-inspired neural networks can be used for DT-HRC applications. In recent years, the advancement of photo-realistic simulation environments such as Nvidia Isaac platforms and physics-inspired neural networks could potentially overcome the limitation faced in the area of DT-HRC. Process simulation and visualization platforms, such as Visual Components (VC), Siemens Simatic WinCC and KUKA.Sim Pro, CoppeliaSim, Gazebo, Siemens Technomatix, programming and computing platforms such as MATLAB and communication frameworks such as ROS/ROS2 could be used for creating the DT of human–robot collaboration. Cloud platforms such as OpenWhisk, WSO2, or OpenShift can be used for data processing.

In technologies related to AR and VR, such as real-time communication, the necessity of realistic representation of the physical system and the environment are also essential for creating a DT. Developments in these fields could bring radical changes in DT technology and its implementation. Game engines are an option worth considering for the visualisation of DT-HRC, with simulation and visualisation of DT-HRC considered as two different aspects. An instance of the DT-HRC process can be created to perform simulations in the background, while the visualisation through game engine tools may provide a real-time update of the process.

There are various concepts and frameworks currently available to develop a DT model. However, a greater focus on creating a generic approach that can serve as a common base for all DT platforms could produce interesting findings as the technology matures. With the advancement of Edge AI or AI-enabled hardware graphical processing units (GPU) such as the Nvidia Jetson series or AI-accelerators such as Intel Movidius products, the DT of a factory level process can be decomposed into smaller DT processes in a modular manner. This allows the processing of information at the lower system level, rather than utilising data at a higher level for parameterizing/tuning the operations. This can unlock different new approaches for building a factory level DT.

The challenge and potential of DT within the manufacturing domain were also discussed in this paper. The challenges around CPS and IoT need to be addressed together with advances in simulation environments with physics engines to achieve the expected benefits of DT. There is also a need for better modelling of complex tasks to build more accurate DTs. In addition, better data transfer between different modules of the DT is essential. Continued progress in the fields of communication and semiconductor processing technologies are key enablers in this regard.

Furthermore, the notion and understanding of DT varies from person to person. Some consider DT as a simulation, for others, it is an emulator that has all the precision of the system being emulated. Therefore, there is no consensus on how to define or consider the DT of a given system. In summary, several questions pertaining to DT technologies still remain to be answered. The major challenges around DT are listed below:

- There are no definite methods to determining the fidelity of the DT platform;
- Various issues and difficulties associated with DT-simulation, as well as with the modelling and visualization, still remain unsolved;
- Lack of standard communication frameworks for handling the multitude of sensor data, avoiding latency and allowing synchronisation to build a real-time DT of a shop-floor.

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